Single cell atlas identifies lipid-processing and immunomodulatory endothelial cells in healthy and malignant breast

Supplementary information

Annotation of luminal and immune cell subclusters

Luminal subcluster annotation – nomenclature was based on a combination of sample origin and gene expression signatures. Clusters L1-5 highly expressed genes involved in hormone receptor signaling (*ESR1, PGR, AR, TFF1, ANKRD30A*), cell proliferation (*TOP2A, BIRC5*), and/or known breast cancer (BC) genes (*GATA3* and *MUC1*) 1,2 (Supplementary Fig. 5a), suggestive of their malignant nature. Interestingly, subcluster L5 showed a gene expression signature resembling malignant epithelial cells in our dataset but was predominantly derived from peritumoral mammary tissue (Supplementary Fig. 5a-d), raising the question of whether this subcluster may consist of breast cancer cells that invaded the surrounding peri-tumoral tissue. Luminal subclusters L6-8, on the other hand, expressed genes known to be expressed in secretory and mature 'healthy' luminal cells (SLPI, ELF5, KIT)^{3,4}, with a low or absent expression of hormone receptor signaling (Supplementary Fig. 5a). Cluster L6 was predominantly derived from the tumoral tissue (Supplementary Fig. 5c) but closely resembled the secretory and mature luminal phenotype (Supplementary Fig. 5a), indicating that noncancerous 'healthy' luminal cells may exist within the TME. This finding is also observed by other groups, but with unclear biological relevance⁵.

We further explored these findings by inferring chromosomal copy number variations (CNVs) from the gene-expression data using the inferCNV algorithm, as described in the previous studies^{6,7}. We selected all immune, fibroblast, myoepithelial and (peri-)vascular cells detected in our dataset as a normal (non-malignant) reference to estimate the presence of CNVs (indicative of malignant cells) in all luminal subclusters. This analysis revealed a dominant gain of the long (q) arm of chromosome 1 in clusters L1 and L2, largely derived from tumoral tissues (Supplementary Fig. 5d). Previous work indeed identified gain of 1q as the most frequent chromosomal arm-level event in gynecologic and breast cancers, occurring in almost 50% of analyzed samples⁸, suggesting that the L1 and L2 subclusters in our dataset are indeed of malignant nature. Other frequently observed CNVs are gain of 8q and loss of 13q⁸, both of which we observed in clusters L3 and L4 (derived largely from tumoral tissue) (Supplementary Fig. 5b,c) again suggesting their likely cancerous phenotype.

Clusters L6-8 did not share these CNVs and instead largely resembled the reference cells, suggestive of their non-malignant nature, and in line with their predominant peri-tumoral origin (Supplementary Fig. 5b,c). The only exception was an observed gain of 11p, uniquely detected in cells derived from peri-tumoral tissues. This particular CNV has also been observed in non-malignant epithelial cells in other studies profiling breast cancer tissue CNVs^{9,10}, and is thus unlikely to reflect a malignant nature of these cells.

Lastly, approximately half of cluster L5 presented with a mixture of CNVs resembling clusters L1-4, whereas the remaining cells resembled clusters L6-8, indeed suggesting this cluster may harbor cancerous cells invading peri-tumoral tissue, as described above.

Immune subcluster annotation – clusters of myeloid or lymphoid immune cells were annotated using canonical marker genes of major immune cell populations and subpopulations, marker genes from other studies employing scRNA-seq on (breast) tumor immune cells, and other available literature¹¹⁻²⁰. In brief, major myeloid subpopulations in the myeloid cell subclusters, containing macrophages, neutrophils, and conventional dendritic

cells, were identified by examining the expression of *CD14*, *CD68*, *C1QA* (macrophages); *S100A8, S100A9, CXCL2* (neutrophils) and HLA-genes, *CD1C*, *CCR7* (dendritic cells). Subpopulations of macrophages were annotated using literature and gene sets for tissueresident-like, TAM, M1- and M2-like macrophages from^{15,16,21-23}. The presence of subtypes of conventional dendritic cells or neutrophils was assessed using literature^{18,24}.

Even though NK cells can originate from lymphoid and myeloid precursors, NK cells and T cells were subclustered together as performed by others²⁵. $\alpha\beta T$ cells were identified by *CD3D*, *CD3E*, *TRAC*, *TRBC2,* and absence of *TRD*/*TRC* genes. *CD4* and *CD8A* expression was used to annotate CD4⁺ or CD8⁺ T cells. CD4⁺ T cell subclusters were identified by assessing expression of markers indicating a naïve/activated/memory phenotype (e.g. *IL2RA*, *IL7R*, *CD44*, *CD69*, *CCR7*, *SELL*), regulatory T cells (e.g. *IL2RA*, *TIGIT*, *FOXP3*), T helper cell genes (Th1/Th2/Th17 canonical transcription factors/cytokines) and using scRNA-seq literature describing T cell heterogeneity in breast cancer¹². Similarly, CD8⁺ T cell subclusters were annotated by assessing expression of markers indicating a naïve/memory phenotype (*IL2RA*/*CD44*/*CD69*/*CCR7*/*SELL*), effector phenotype (cytotoxic T cell markers, such as *GZMB*, *PRF1*, *IFNG*, *TNF*), or markers whose high expression is associated with an exhausted state (e.g. *PDCD1*, *HAVCR2*, *LAG3*). Tissue-resident memory T cells were identified using literature26,27. and by assessing the expression of *ZNF683*, *PRDM1*, *ITGA1*, *CXCR6*, *ITGAE*, *CD69* and downregulated expression of *CD28*27. NK cell subclusters, lacking T cell genes, were annotated based on the expression of *NKG7*, *KLRB1*, *KLRF1*, *NCAM1,* and *FCGR3A* and gene expression of cytolytic effector molecules such as *GZMB* and *PRF1*, chemokine expression (*XCL1, XCL2*) and using a cross-species NK cell taxonomy¹⁴.

Supplementary Figures

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CD105

Supplementary Fig. 1: Single cell taxonomy of endothelial cells in the breast. a UMAP-plots, color-coded for the expression of representative marker genes in EC subclusters. Red arrows indicate cells highly expressing the marker gene. Color scale: red – high expression, blue – low expression. **b** Composition of EC subtypes in peri-tumoral (pEC) and tumoral (TEC) breast samples per patient. To correct for differences in absolute numbers of tumoral *versus* peritumoral cells, numbers in each subcluster were divided by the total number of tumoral and peri-tumoral cells, respectively (relative representation). Left: Relative contribution of each phenotype scaled to 100%. Right: Contribution of each phenotype in absolute numbers; the total number of analyzed ECs on the right. Bottom panel: relative contribution of ECs per condition, color coded per subcluster. EC – endothelial cell, LS – lower sequencing depth, PCV – post-capillary venule. **c** Pseudotime trajectory of arteries, capillaries, and veins, color coded according to cluster origin. PC – principal component. **d** Pseudotime analysis represented by loess regression-smoothened gene expression of indicated marker genes of arteries, capillaries, and veins, color coded according to subcluster. **e** Representative micrographs of human breast peri-tumoral (top) and tumoral (bottom) tissue sections, immunostained for CD105, INSR and counterstained with Hoechst (n=3). Lower panels: magnifications of the boxed areas in the upper panels. Scale bar: 50 µm. **f** Representative micrographs of human breast peri-tumoral (top) and tumoral (bottom) tissue sections, immunostained for CD105, CD36, and counterstained with Hoechst (n=3). Lower panels: magnifications of the boxed areas in the upper panels. Scale bar: 50 µm. **g** Representative micrographs of human breast peri-tumoral (top) and tumoral (bottom) tissue sections, immunostained for CD105, ACKR1, smooth muscle actin (SMA) and counterstained with Hoechst (n=3). ACKR1 is detectable in thin-walled SMA-negative (presumably) veins/venules. Lower panels: magnifications of the boxed areas in the upper panels. Scale bar: 50 µm.

Supplementary Fig. 2: Expression of microvascular mutually exclusive markers. a-c Spatially restricted expression of *ID2* and *FABP4*, top-ranking marker genes of capillary i (EC11) and capillary ii (EC12) subclusters, respectively. Representative images of a human breast tissue section are shown, immunostained for CD105 (green) and counterstained with Hoechst (blue). Microvascular ECs exclusively expressing *FABP4* (a; red, RNAscope) or *ID2* (b; white, RNAscope), or expressing both *FABP4* and *ID2* (c) are shown. Right panels: magnifications of the boxed areas in the left panels. Arrows point at *ID2*⁺ *FABP4*- ECs. Scale bar: 25 µm, n=8.

Supplementary Fig. 3: EC transcriptomic heterogeneity & congruency. a Dot plot of top-25 most upregulated pathways per EC subcluster, as calculated by GO enrichment analysis (ClusterProfiler), using a p-value cut-off of < 0.01, and a q-value (Benjamini-Hochberg) cut-off of < 0.05. Color scale indicates adjusted p-value; dot size depicts the number of enriched genes within each GO term; GO terms associated with distinct clusters are shown in bold. Abbreviations: Ag – antigen, APP – antigen processing and presentation, cell. – cellular, detox. – detoxification, EC – endothelial cell, EP – epithelial, FA – fatty acid, IFN – interferon, LDL – low-density lipoprotein, LP – lipoprotein, LS – lower sequencing depth, MHC-II – MHC class II, morphog. – morphogenesis, neg. – negative, PCV – post-capillary venule, pos. – positive, PS – polysaccharide, reg. – regulation, resp. – response. **b** Subcluster identity of breast ECs (n=850) that were unassigned by the scmap projection in Fig. 2a. LS – lower sequencing depth. **c** Volcano plot showing differential gene expression analysis of pEC veins *versus* TEC veins. Key pEC-enriched marker genes involved in immunoregulation are indicated. Gray, significant (adjusted p-value < 0.05); dark blue, not significant. Differential expression analysis was performed using *limma*, the magnitude of differential expression (log2 fold change) and false discovery rate adjusted p-values (calculated with the Benjamini-Hochberg method) are provided on the x- and y-axis, respectively.

Supplementary Fig. 4: The breast microenvironment. a UMAP-plots of representative marker genes in the different major cell types. Red arrowheads indicate cells highly expressing the marker gene. Color scale: red – high expression, blue – low expression. **b** UMAP-plots of all 18,082 cells, color-coded by condition (peri-tumor (gray), tumor (red)). **c** Abundances of major cell types across conditions (peri-tumor (gray), tumor (red)), x-axis depicts major cell types color coded as in Fig. 3c. pDC – plasmacytoid dendritic cells, PV – perivascular, NK – natural killer. Data are mean ± SEM, n=8 for peri-tumoral samples and n=9 for TME samples, **p<0.01 (exact p-value=0.0053), a separate paired t-test (two-tailed) per major cell type (considering the 8 complete pairs). **d** Composition of major cell types in peri-tumoral (top panel) and tumoral (bottom panel) breast samples from individual patients. Left: Relative contribution of each phenotype scaled to 100%. Right: Contribution of each phenotype in absolute numbers; the total number of analyzed cells on the right. EC – endothelial cell, NK – natural killer, DC – dendritic cell. **e** Representative micrographs of human breast peri-tumoral and tumoral tissue sections, stained with hematoxylin and eosin (n=8). Scale bar: 100 µm. Arrowheads indicate cell types (blue, lymphocytes; purple, myeloid cells; red, blood vessels; green, myoepithelial cells; yellow, fibroblasts; gray, adipocytes). **f** Representative micrographs of human breast peri-tumoral and tumoral tissue sections, immunostained for breast epithelium (CK8/18), myoepithelial cells (CK5/6), T cells (CD3), and macrophages (CD68). Scale bar: 100 µm (n=8). **g** Abundances of major cell types in peri-tumoral and tumor tissue from BC patients, as quantified on H&E and immunostained sections; color coded per condition. Data are mean ± SEM, n=8, *p<0.05, **p<0.01 (exact p-values= 0.0029, 0.0335 and 0.0228, respectively), separate paired t-test (two-tailed) per cell type.

Supplementary Figure 5

s myoepithelial cells 3

LIMAP-1

Supplementary Fig. 5: transcriptomic heterogeneity in the breast: epithelial cells. a Violin plots of the expression level of the indicated genes involved in hormone receptor and signaling pathways (*ESR1, PGR, AR, TFF1, ANKRD30A*); proliferation (*TOP2A, BIRC5*), BC markers (*GATA3, MUC1*), and breast maturation (*SLPI, ELF5, KIT*) in luminal subclusters. **b** Pie chart showing the sample origin (tumor- or peritumor) of luminal subclusters. Annotation is based on expression profile as indicated in panel a. **c** Composition of luminal subclusters in peri-tumoral and tumoral breast samples per patient. **d** Copy number profiles estimated from the scRNA-seq data (inferCNV analysis). Columns correspond to genes, ordered by chromosome position, rows correspond to cells. Top heatmap: reference cells, used to define baseline expression; all immune, fibroblast, myoepithelial and (peri-)vascular cells detected in our dataset were selected as a normal (non-malignant) reference. Bottom heatmap: reference cell expression data (top heatmap) is subtracted from the luminal cell expression data to yield differential/residual expression values; red indicates chromosomal region amplification; blue indicates chromosomal region deletion. Cells are clustered by luminal subcluster. **e** UMAP-plot of myoepithelial cells, color-coded by subcluster. **f** Heatmap of the expression levels of the top 10 marker genes in myoepithelial cell subclusters. Color scale: red – high expression, blue – low expression. **g** UMAP-plots of representative marker genes in the different myoepithelial cell subclusters. Red arrowheads indicate cells highly expressing the marker gene. Color scale: red – high expression, blue – low expression. Abbreviations: NK – natural killer, Myo – myoepithelial.

Supplementary Figure 6

Supplementary Fig. 6: transcriptomic heterogeneity: perivascular and other stromal cells. a UMAP-plot of perivascular stromal cells, color-coded by subcluster. LS – lower sequencing depth. **b** Heatmap of the expression levels of the top 10 marker genes in perivascular stromal cell subclusters. Color scale: red – high expression, blue – low expression. LS – lower sequencing depth, PV – perivascular. **c** UMAP-plots of representative marker genes in the different subclusters in perivascular stromal cells. Red arrowheads indicate cells highly expressing the marker gene. Color scale: red – high expression, blue – low expression. **d** UMAP-plot of other stromal cells annotated as fibroblasts, color-coded by subcluster. ASC – adipocyte stem cell, LS – lower sequencing depth. **e** Heatmap of the expression levels of the top 10 marker genes in fibroblast subclusters. Color scale: red – high expression, blue – low expression. **f** UMAP-plots, showing expression of representative marker genes in the different subclusters of other stromal cells. Red arrowheads indicate cells highly expressing the marker gene. Color scale: red – high expression, blue – low expression.

COL18A1

APF

GAS6 EFNB2

TELEVISION п

Predicted target genes in angiogenic ECs (tumor)

SHIP

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Supplementary Fig. 7: Details on immune cell subclustering and RLI prediction. a UMAPplots showing expression of representative marker genes in the different T-/NK cell subclusters. Color scale: red $-$ high expression, blue $-$ low expression. Red arrowheads indicate cells highly expressing the marker gene. **b** Contribution of tumoral and peri-tumoral cells to each T-/NK cell subcluster. Left: Relative contribution of each phenotype scaled to 100%. Right panel: contribution of tumoral and peri-tumoral cells in absolute numbers (absolute representation); total number of analyzed cells on the right. NK – natural killer. **c** UMAP-plots of peri-tumoral and tumoral T-/NK cells, color-coded by condition. **d** Contribution of individual patient samples to each T-/NK cell subcluster. Left: relative. Right: absolute. **e** UMAP-plots showing expression of representative marker genes in the different myeloid subclusters. Color scale: red $-$ high expression, blue $-$ low expression. Red arrowheads indicate cells highly expressing the marker gene. **f** Contribution of tumoral and peri-tumoral cells to each myeloid cell subcluster. Left: relative. Right: absolute; total number of analyzed cells on the right. TAM – tumor associated macrophages, $TR -$ tissue resident, $LS -$ lower sequencing depth. **g** UMAP-plots of peri-tumoral and tumoral myeloid cells, color-coded by condition. **h** Contribution of individual patient samples to each myeloid cell subcluster. Left: relative. Right: absolute. **i (Top panel)** NicheNet analysis showing prioritized ligands (left) expressed in angiogenic ECs predicted to regulate target genes in myeloid cells. Ligands were ranked by their likelihood of regulating target genes in tumoral *versus* peri-tumoral samples. Predicted ligand–target matrix denoting the regulatory potential between ligands (y-axis) expressed in angiogenic ECs, and target genes (x-axis) expressed in tumoral myeloid cells is shown on the right. Color scale: dark red/brown, high regulatory potential score; light red/brown, low regulatory potential score. **(Bottom panel)** NicheNet analysis showing prioritized ligands (left) expressed in conventional DCs (cDCs) predicted to regulate target genes in angiogenic ECs. Ligands were ranked by their likelihood of regulating target genes in tumoral *versus* peri-tumoral samples. Predicted ligand–target matrix denoting the regulatory potential between ligands (y-axis) expressed in cDCs, and target genes (x-axis) expressed in tumoral angiogenic ECs is shown on the right. Color scale: dark red/brown, high regulatory potential score; light red/brown, low regulatory potential score.

COPA[¥]

Supplementary Fig. 8: Additional information to the receptor ligand interaction predictions.

a Representative micrographs of human breast tumoral tissue sections, immunostained for CD105 (magenta), FOXP3 (white), INSR (yellow), PODXL (green), SELL (red) and counterstained with Hoechst using Akoya's Opal™ Multiplex IHC system (n=9). Dotted green line delineates ECs, dotted white lines surround FOXP3⁺ cells. Scale bar: 25 µm. Right panels show magnifications of boxed areas. **b** Quantitative real-time PCR showing *CLEC2B* KD efficiency in HUVECs. Color-coded per control or KD-construct (gray PLKO, green CLEC2B^{KD}, blue CLEC2B^{KD2}). Data are mean \pm SEM, n=3, *** p<0.001 (exact p-values = 0.0007 and 0.0005, respectively). One-way ANOVA with correction for multiple comparisons (Dunnett's). KD – knock down. **c** Densiometric quantification (left) and representative immunoblot (right) showing CLEC2B KD efficiency at the protein level in HUVECs. Color-coded per control or KDconstruct (gray PLKO, green CLEC2B^{KD}, blue CLEC2B^{KD2}). For calculation of the % reduction in CLEC2B expression relative to CTRL, the CLEC2B/housekeeping gene ratio in the CLEC2BKD conditions was determined separately for every HUVEC donor analyzed, and normalized to the CLEC2B/housekeeping gene ratio in the CTRL condition (in the same donor); alpha-Tubulin or GAPDH were used as housekeeping genes. Data are mean ± SEM, n=4, ***p<0.001, ****p<0.0001 (exact p-values= <0.0001 and 0.0003, respectively). One-way ANOVA with correction for multiple comparisons (Dunnett's). **d** Quantitative real-time PCR showing *CLEC2B* expression in HUVECs upon treatment with LPS (pink) and LPS+IFNγ (blue). Data are mean ± SEM, n=3, *p<0.05 (exact p-value=0.0445). One-way ANOVA with correction for multiple comparisons (Dunnett's). **e** Quantification of NK degranulation (as measured by the percentage of CD107a⁺ NK cells) after co-culture for 24h with LPS-IFNγ-treated HUVECs. Color-coded per control or KD-construct (gray PLKO, green CLEC2B^{KD}, blue CLEC2B^{KD2}). Data are mean ± SEM, represented as a fold change, n=6, ****p<0.0001 (exact p-values= <0.0001). One-way ANOVA with correction for multiple comparisons (Dunnett's). **f** Circos plots representing RLI analysis between immune cells and angiogenic/venous ECs. Ligand is expressed on immune cell subclusters, receptor is expressed on angiogenic (left panel) or venous ECs (right panel). Plots are color-coded for receptor-ligand pairs (inner circle, arrows, gene names) and immune cell subclusters expressing the ligand (bars perpendicular to the inner circle). RLI pairs considered novel between ECs and specific immune cell clusters/subtypes are indicated in bold (genes) and with asterisks (subclusters).

CRC
=2223

● vein iv
● activated PCV
● angiogenic: LS
● lymphatic
● unassigned

 0.5
scmap similarity index

Supplementary Fig. 9: Transcriptomic heterogeneity of breast EC metabolism. a Representative micrographs of human breast tissue on the interphase between tumor (left) and peri-tumor (right), immunostained for CD105, FABP4 and counterstained with Hoechst (n=7). Yellow dotted line indicates putative tumor border. Lower panels: magnifications of the boxed areas in the upper panels. Light blue asterisks indicate representative putative adipocytes, which (besides LIPECs) are also positive for FABP4. Light blue arrows indicate FABP4+ ECs. Scale bar: 100 µm. **b** UMAP-plot of marker gene expression (*LPL, NR1C3 (PPARG*)) (left two panels) or *NR1C3 (PPARG*) and *LXRA* (*NR1H3*) regulon activity predicted by SCENIC analysis (right two panels; numbers between brackets indicate the number of genes within the regulons for the respective transcription factor). Color scale: red – high expression, blue – low expression. **c** Representative micrographs of human breast tumor tissue sections in nondiabetic (left; n=8) or diabetic (middle; n=8) control BC patients and in (diabetic; n=9) BC patients pre-treated with metformin (right), showing combined immunostaining for CD105 with *in situ* hybridization (RNAscope) for *FABP4* and *PPARG* and counterstaining with Hoechst. Right & bottom panels: magnifications of the boxed areas in the main left panels. Orange arrowheads indicate (nuclear) *PPARG* in *FABP4*⁺ ECs. Scale bar: 10 µm. **d** Sankey diagram (left panel), showing the assignment of EC subclusters (identified in our in-house generated breast EC taxonomy) to unannotated breast cancer (BC), ovarian cancer (OVC) or colorectal cancer (CRC) tumoral (TEC) and normal (peri-tumoral, pEC) ECs from Qian et al. $(2020)^{23}$ (n = 5438 ECs). BC, OVC and CRC ECs are visualized on the left; cluster projections are visualized on the right (color-coded according to the breast EC taxonomy subclustering, see legend on the right). Box plots (right panel) depict the scmap similarity index. Boxes extend from the 25th to $75th$ percentiles, line in the middle of the box is plotted at the median. Whiskers = min and max. LS – lower sequencing depth, PCV – post-capillary venules.

Supplementary Fig. 10: FACS gating strategy for sorting human breast tissue ECs. Representative sequential FACS data and sorting gates for dissociated human breast (cancer) cells. The final sort for the EC-enriched fractions was of viable single cells from the CD45- /EpCAM⁻/CD31⁺/CD102⁺ compartment (right panel). For pME and TME (without ECenrichment) fractions, viable single cells were sorted (third panel, bold). Percentages reflect the fraction of the (previous) parent population.

Supplementary Table 1

Supplementary Source Data File

Raw blots used in Supplementary Figure 8c whole blot

Representative image in Supplementary Figure 8c; cut blot

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